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MODELLING THE IMPACT OF BIOGAS PRODUCTION CAPACITY AND INDUSTRIAL DETERMINANTS ON ELECTRICITY CONSUMPTION IN AGRICULTURE

Purpose. *The paper aims to explore the relationships between biogas production capacity, economic, technological, and natural-resource factors, and electricity consumption in the agricultural sector of Ukraine and the EU countries.*

Methodology / approach. *The study uses fixed effects panel econometric models to account for temporal and institutional heterogeneity in the data. The investigation is conducted for Ukraine and the EU countries, such as Germany, France, Italy, and Poland. The research is based on correlation and regression analysis using econometric modelling. The model includes indicators such as agricultural export and import, farmland area, crop and livestock production volumes, and the installed capacity of biogas plants. The Box-Cox transformation, normality tests (Jarque-Bera and Shapiro-Wilk), multicollinearity, and homoscedasticity tests (Breusch-Pagan and White) were applied to validate the model.*

Results. *The modelling results for Ukraine indicate considerable potential for reducing electricity consumption in the agro-industrial sector through the development of biogas technologies. In this context, sustainable reduction scenarios are proposed for Ukraine based on investments in renewable energy. Observations for several EU countries with high biogas production levels suggest a tendency toward lower agricultural energy intensity; however, this relationship should be interpreted with caution, as it requires further empirical verification. A negative and statistically significant coefficient for Poland indicates that, under comparable levels of biogas-based electricity generation and export intensity, Poland's agricultural sector tends to consume less electricity than the benchmark country (Germany), potentially reflecting more favourable structural or technological conditions for energy efficiency.*

Originality / scientific novelty. *The novelty lies in developing and empirically validating a comprehensive model for assessing the impact of agribusiness on electricity consumption, with a specific focus on the role of biogas. Unlike existing studies, this article integrates economic, technological, and energy indicators to measure the complex interactions affecting energy consumption in agriculture.*

Practical value / implications. *The results can inform energy management policies in agriculture, particularly in supporting renewable energy integration. The findings are relevant for government agencies, local authorities, agribusinesses, and international stakeholders in developing strategies for sustainable rural energy transitions and enhancing energy security.*

Key words: *energy consumption, biogas, renewable energy, econometric modelling, energy efficiency, decarbonisation, sustainable development.*

1. INTRODUCTION

The study of electricity production and consumption by sector is critically important for ensuring energy security, effective planning and sustainable economic development. Understanding the structure of electricity production and consumption allows us to identify the economy's dependence on various energy resources and assess its vulnerability to external and internal factors.

The energy sector is the most sensitive to indirect economic benefits changes, particularly in the northwest and southwest of the world, while agriculture and industry are more sensitive in the central region, emphasising the importance of region-specific emission reduction strategies (Mlaabdal et al., 2024). The analysis of the energy sector of Ukraine indicates the need to increase resilience and strengthen energy security by diversifying energy sources and introducing energy-saving technologies (Kasianenko et al., 2024; Horák et al., 2023; Huang et al., 2025). In turn, studying electricity consumption by sector helps identify industries with high energy intensity and develop strategies to improve their energy efficiency (Zadorozhnyi et al., 2023; Kurmanov et al., 2025). Analysis of electricity production by sector allows us to assess the potential and effectiveness of renewable energy deployment. In particular, the experience of Italy, which ranks fourth in terms of electricity consumption in the EU, demonstrates the importance of supporting the production of "green" electricity to ensure energy independence and environmental sustainability (Dzwigol et al., 2024).

The energy sector has a significant impact on the economy and the labour market. In Ukraine, in 2018–2019, the energy industry generated about 8% of GDP, and as of 2024 it employed approximately 450 thousand people, which is around 3% of the population (UkraineInvest, 2024). Understanding electricity production and consumption by sector allows for effective planning of economic policies and development strategies (Drebot et al., 2023). In turn, a study showed how energy restrictions affect the functioning of the industry and the country's economic performance (Bi et al., 2025; van der Zwaan et al., 2025; Li et al., 2024). Research into electricity production and consumption by sector is fundamental to ensuring energy security, improving economic efficiency, and developing sustainable development strategies. Electricity is a key resource for the functioning of a modern economy and the development of the agricultural complex. It ensures the efficiency of production processes, the competitiveness of enterprises and technological progress (Li et al., 2024; Wen et al., 2024; Rosenow et al., 2022). Research on electricity consumption in the agricultural sector is strategically crucial for increasing the agricultural sector's efficiency, reducing costs, implementing environmental standards, and developing renewable energy. Optimal use of electricity ensures the economic competitiveness of enterprises, reduces dependence on traditional energy sources, and contributes to the sustainable development of the agricultural sector.

The scientific novelty of this study lies in the development and empirical validation of a comprehensive approach to assessing the impact of agro-industrial activities on electricity consumption in Ukraine, with a particular focus on the role of biogas production as an alternative energy source. Unlike existing studies that focus on optimising energy use in the agro-industrial complex or analysing the influence of various technologies and strategies on the sustainable development of agriculture, this article uses correlation regression analysis to identify the impact of different determinants on electricity consumption in the agricultural sector. Thus, this article aims to examine the interrelationships between installed biogas production capacity, economic, technological, and natural-resource factors, and electricity consumption in Ukraine's agricultural sector. The proposed study fills a theoretical gap by developing a scientific approach for a comprehensive assessment of the impact of agro-industrial activity on electricity use, identifying key drivers of increasing energy demand, and exploring opportunities to enhance energy efficiency and promote the use of alternative energy sources through the application of correlation and regression analysis methodology.

The article is structured as follows: a literature review that explores scientific approaches and processes for optimising energy consumption in the agricultural sector; a methodology section that describes the research methods, variables, and data sources used to test the research hypothesis linking electricity consumption in agriculture and the environmental dimension of efficiency; a results section that interprets the obtained empirical findings; a discussion section that compares the results with the conclusions of existing studies; and a conclusion that summarises the article's findings, practical implications; limitations, and directions for future research.

2. LITERATURE REVIEW

2.1. Models for decarbonisation in the agricultural sector. Scholars pay significant attention to researching ways to optimise energy consumption in the agricultural complex and applying economic tools to stimulate it (Jawad et al., 2025; Zhang et al., 2025; Wang et al., 2023).

A growing body of research focuses on understanding the relationship between production factors, technological development, renewable energy integration, and electricity consumption in the agricultural sector, often using correlation and regression analysis to quantify these links. Rokicki et al. (2021) examined electricity consumption patterns in the agricultural sectors of the EU countries from 2005 to 2018, applying correlation analysis to assess the relationship with economic performance indicators. The study found that an 85% increase in renewable energy consumption significantly influenced overall agricultural electricity demand, highlighting the role of policy and investment in renewable energy deployment in reducing dependency on fossil fuels. Dyvak et al. (2025) developed regression models to predict biogas production volumes based on technological parameters such as pH levels and feedstock composition. Their results confirmed that regression analysis is an effective method for forecasting renewable energy output and optimising production processes in agriculture. Earlier, Karkacier (2006) analysed the effect of energy use on agricultural productivity in Turkey, using multiple regression analysis. The results indicated decreasing marginal productivity of energy inputs per hectare, suggesting structural and technological changes in agricultural practices. From a broader macroeconomic perspective, Hao (2022) investigated the interlinkages between renewable energy consumption, production, exports, and CO_2 emissions in China using econometric methods including cointegration, causality testing, and VAR modelling. The study concluded that renewable energy development has a bidirectional long-term relationship with economic activity, contributing to carbon reduction goals. Simultaneously, Bekun & Alola (2022) applied an ARDL model with panel data for African countries to examine the role of economic activity in renewable energy consumption. The findings showed that agricultural activity positively affects renewable energy use in the long run, with an elasticity coefficient of approximately 0.252, underscoring agriculture's role in fostering renewable energy adoption. The study (Huang et al., 2025) examines the economic benefits of energy-related emission reduction actions under China's carbon neutrality goal. Using an Adaptive Multi-Regional Input-Output model, the authors show that changes in energy consumption will lead to indirect economic benefits, which will peak around 2040.

Thus, these studies provide strong empirical evidence that integrating renewable energy, particularly biogas, into the agricultural sector is both technically feasible and economically beneficial. Moreover, the consistent application of correlation and regression methods across these works reinforces the validity of the approach used in the present study.

2.2. Renewables development in the Ukrainian agricultural complex. In 2024, trends in resource conservation and energy efficiency in agriculture continue to develop actively. According to the latest data, investments in modern developments aimed at the rational use of resources are increasing worldwide, indicating an ongoing interest in implementing effective solutions (Loschke et al., 2025; Chygryn and Khomenko, 2024). In Ukraine, there has also been a significant increase in the use of renewable energy sources. In particular, the capacity of solar power plants was planned to increase to 500 MW by the end of 2024 (Martins, 2024). This is an essential part of the sustainable development strategy based on resource-saving technologies in agriculture as the foundation for future success. Ukraine's agricultural complex is moving towards energy efficiency and renewable energy sources. Considering global environmental challenges, the increase in the cost of traditional energy sources and the need to increase the agricultural sector's competitiveness, alternative energy is becoming an important direction of development. The development of biogas production in Ukraine is strategically vital for energy security, environmental sustainability, and the increase of the economic efficiency of the agricultural complex. Biogas technologies allow for the effective utilisation of organic waste from agriculture, reduce dependence on imported energy sources and contribute to the decarbonisation of the economy. Ukraine has a huge resource potential for biogas production thanks to a developed agricultural sector: over 100 million tons of organic waste annually (manure, silage, husks, food waste), a large number of livestock farms that can use manure for biogas plants, a developed infrastructure for growing energy crops (corn silage, sorghum), which can be used for biogas production. According to the Dixigroup report, under favourable conditions, biogas production in Ukraine could reach 1 billion cubic meters per year in 2030, 4.5 billion cubic meters per year in 2040, and 20 billion cubic meters per year in 2050. At the same time, at the end of the forecast period, half of the produced biogas could be consumed domestically (Forum Energii, 2024). Biogas plants provide an autonomous energy supply for enterprises, reducing electricity and gas costs. In addition, the transition of agricultural enterprises to biogas saves up to 40% of energy consumption costs. Biogas production reduces methane and CO_2 emissions, which is critically essential for combating climate change, and purified biogas can replace natural gas, reducing carbon emissions by up to 85%.

The hypothesis of the paper: there is a statistically significant relationship between the level of agricultural development (specifically, the volumes of imports, livestock production, and biogas capacity) and electricity consumption in Ukraine's agricultural sector. In particular, increased import volumes and livestock production contribute to higher electricity consumption.

The research question of the paper: can biogas development reduce the dependence of agricultural enterprises on external electricity supply, and how significant is its role in the context of sustainable rural energy transitions?

3. METHODOLOGY

For a comprehensive analysis of the factors influencing electricity consumption in the agricultural sector, it is essential to use relevant economic, production, and energy indicators. This study uses the following indicators: agricultural export, agricultural import, agricultural land area, crop production volume, livestock production volume, and the installed capacity of biogas production. A high level of agricultural exports requires extensive post-harvest processing, including drying, sorting, packaging, and transportation, which increases electricity consumption. In turn, the processing of export-oriented products (e.g., flour or oil production) is also energy-intensive (Wróbel-Jędrzejewska et al., 2024; Van Kernebeek et al., 2016). Monitoring export dynamics helps to forecast future loads on the power grid in the agricultural sector. Conversely, a high level of imports may indicate a low level of domestic production, which can reduce overall agricultural electricity consumption. However, importing certain goods (e.g., compound feed and seeds) may contribute to developing local livestock or crop production, thereby increasing electricity consumption (Gatto et al., 2024; Reinsch et al., 2023). Another determinant that can influence energy consumption is the area of agricultural land, as larger areas may stimulate the development of intensive farming (e.g., greenhouses, hydroponics), which requires more electricity. The expansion of cultivated and irrigated land, in turn, requires more machinery, equipment, and energy-intensive pumping stations. High crop yields lead to larger harvesting volumes and post-harvest processing (cleaning, drying, and storage), increasing electricity consumption. Dependence on modern technologies such as drip irrigation, microclimate control, and fertigation further increases energy demand (Soussi et al., 2025). Additionally, increased crop production stimulates bioenergy development, including using biomass for electricity generation. At the same time, livestock complexes are among the most energy-intensive facilities due to the need for lighting, ventilation, heating, automated feeding, and milking. Large farming enterprises use refrigeration systems to store milk and meat, increasing electricity consumption. Depending on the level of livestock development, it is possible to forecast the energy load on the power system in agricultural regions. Biogas plants generate electricity, which can reduce the need for external electricity supply for agrarian enterprises (Tryhuba et al., 2025). A high level of biogas generation contributes to the energy independence of farming operations while assessing the installed capacity of biogas facilities, which allows for evaluating the energy balance of the agricultural sector and the potential for replacing traditional energy sources (Burg et al., 2025; Paris et al., 2022).

The application of such indicators enables a comprehensive assessment of the impact of agricultural activity on electricity consumption, identification of the key drivers of increasing energy demand, and the discovery of opportunities for improving energy efficiency and using alternative energy sources. These indicators systematically analyse the agricultural sector's influence on energy consumption, which is essential for effective energy resource planning and agricultural development.

The description of the variables used in the econometric model is presented in Table 1.

Table 1

Model variables for Ukraine

Variable	Symbols	Measurement unit	Data sources
Electricity consumption in the agricultural sector	electricity	million MWh	SSSU
Export of agricultural products	export	thousand USD	SSSU
Import of agricultural products	import	thousand USD	SSSU
Agricultural land area	area	thousand hectares	SSSU
Crop production	crops	thousand tons	SSSU
Livestock production	livestock	thousand tons	SSSU
Installed biogas production capacity	biogas	MW	SSSU

Note. SSSU – State Statistics Service of Ukraine.

Source: created by the authors.

The selection of explanatory variables in the model reflects both the installed biogas production capacity and structural characteristics of Ukraine's agricultural sector that are relevant to electricity consumption. Export of agricultural products serves as a proxy for production intensity and competitiveness, as higher export volumes are typically associated with more energy-intensive agricultural activities. Import of agricultural products may indicate structural shifts in domestic production, seasonal deficits, or reductions in energy-intensive operations, thus indirectly relating to technological efficiency and energy demand. Agricultural land area captures the basic production potential, as larger cultivated areas generally require greater energy inputs for mechanised operations and irrigation. Crop production represents the output of plant-based agriculture, which is directly linked to energy use for planting, maintenance, and harvesting processes. Livestock production reflects the scale of animal husbandry, a subsector with considerable electricity needs for lighting, ventilation, milking, and feed preparation. Finally, installed biogas production capacity is included as an indicator of renewable energy integration in agriculture, influencing the energy mix and potentially reducing dependence on conventional energy sources.

While the value-based measurement of crop production can capture market-related aspects such as price fluctuations and monetary output, the use of physical units (thousand tonnes) in this study was chosen to ensure consistency and comparability across time and between countries. Value-based indicators are highly sensitive to inflation, exchange rate volatility, and global commodity price changes, which may distort the relationship between production volume and electricity consumption. By contrast, measuring crop production in physical terms reflects the actual scale of output, which is more directly linked to energy use in production processes such as sowing, cultivation, irrigation, and harvesting. Furthermore, physical units reduce the risk of statistical bias introduced by market shocks, allowing the model to capture the technological and operational aspects of agricultural energy demand more accurately.

The object of the research is the agricultural sector of Ukraine. The study period (2012–2023) was chosen to enable the analysis of long-term changes in the structure of agricultural production and energy consumption, including key stages of energy policy transformation, the growing importance of renewable energy sources, and the challenges caused by military aggression. This temporal and spatial framework makes it possible to identify the key factors influencing electricity consumption in Ukraine's agricultural sector, mainly agrarian imports, livestock production development, and biogas capacity expansion. In addition, 2010–2012 marked the launch of national policy support for regulating biogas production. In 2010, the National Energy Regulatory Commission introduced a "green tariff" for electricity generated from biogas. In 2011–2012, significant amendments were made to the Law of Ukraine, "On the Electric Power Industry," which provided financial incentives for investors in biogas facilities (Verkhovna Rada …, 1997). Starting in 2012, the construction of the first large-scale industrial facilities in the agro-bioenergy sector began to accelerate. 2012–2014 witnessed the initial growth in actual biogas production capacity, characterised by the emergence of the first industrial biogas plants in agriculture, particularly at large livestock enterprises (such as dairy farms and pig complexes). At the same time, the State Agency on Energy Efficiency and Energy Saving of Ukraine launched the Energy Portal, which began systematically recording installed capacity and electricity generation in megawatts. Since 2012, official statistics have been available regarding the installed capacity of biogas facilities, the volumes of energy produced, and the dynamics of new project development.

The nature of the relationship between the consumption of electricity in the agricultural sector and influential factors was determined based on correlation and regression analysis using the econometric model:

$$electricity_i = \beta_0 + \beta_1 \cdot export_i + \beta_2 \cdot import_i + \beta_3 \cdot area_i + \beta_4 \cdot crops_i + \\ + \beta_5 \cdot livestock_i + \beta_6 \cdot biogas_i + \varepsilon_i, \tag{1}$$

where $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ – model parameters;

$i = 1, \dots n,$ – number of observations.

A statistical analysis was conducted to detect observation anomalies. The Jarque-Bera and Shapiro-Wilk tests were used to assess whether the model variables follow a normal distribution. The null hypothesis stated that the variables are normally distributed. The commonly accepted significance level (p-value threshold) for both tests is 0.05. If the p-value exceeds 0.05, the null hypothesis is accepted, indicating that the variable's distribution does not significantly deviate from normality. The Jarque-Bera test statistic is based on the difference between the sample skewness and kurtosis and their expected values under the assumption of normal distribution. In contrast, the Shapiro-Wilk test computes a W-statistic, which is compared to a critical value to determine normality. While the Jarque-Bera test is more suitable for large sample sizes, the Shapiro-Wilk test is considered more reliable when the number of observations is small, as in this study.

For variables that deviated from the normal distribution, null hypotheses (H_0) concerning the optimal Box-Cox transformation parameter were tested, in order to determine whether a transformation would normalise the data:

$\lambda=1$ – transformation is not needed because its results are identical to the original data.

$\lambda=0$ – logarithmic transformation is required.

$\lambda=-1$ – inverse transformation is needed.

Testing null hypotheses made it possible to determine how the model variables should be transformed to conform to the normal distribution (logarithmic transformation, inverse transformation or none).

The next step involved analysing the correlation between the explanatory variables and the model's dependent variable. The Pearson correlation coefficient was used to measure the linear relationship between two continuous variables.

The econometric model was parameterised using the ordinary least squares (OLS) method, which provides the best linear unbiased estimates (BLUE) under classical regression assumptions.

The quality of the constructed econometric model was determined based on the adjusted coefficient of determination R^2_{adj}, which measures the proportion of the total variance in the dependent variable *electricity* that is explained by the variables *export*, *import*, *area*, *crops*, *livestock*, *biogas* after taking into account the degrees of freedom lost due to the inclusion of these variables in the regression, and the Fisher's *F*-test, which measures the joint significance of the parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ of the econometric model.

A critical assumption underlying the application of the OLS method is the homoscedasticity of residuals, which ensures that the estimators obtained are the best linear unbiased estimators (BLUE) within the framework of the Gauss-Markov theorem. To assess the validity of this assumption in the constructed econometric model, diagnostic tests for heteroscedasticity were conducted using both the Breusch-Pagan and White tests. The presence of heteroscedasticity would compromise the efficiency of OLS estimators and may necessitate the use of robust or generalised least squares techniques.

To evaluate the potential multicollinearity among explanatory variables, which could distort coefficient estimates and inflate standard errors, the variance inflation factor (VIF) was calculated. A commonly accepted threshold value of VIF = 5 was applied to detect problematic levels of collinearity.

The assumption of normality of residuals, essential for the validity of inference in small samples, was examined using the Jarque-Bera and Shapiro-Wilk tests. Furthermore, the interpretation of the estimated model parameters was carried out using an elasticity-based approach, which facilitates understanding of the relative responsiveness of the dependent variable to changes in explanatory variables.

The integration of empirical data and comparative calculations from selected EU member states, in particular Germany, Italy, France, and Poland, serves to enhance both the scientific rigour and practical relevance of the research. These countries were selected due to their established experience in implementing renewable energy policies, particularly in the agricultural sector, as well as their diverse trajectories in integrating biogas technologies into national energy frameworks.

Inclusion of international data allows for a broader analytical scope and contributes to the positioning of the research within a transnational context. Comparative analysis enables the identification of common trends and divergences in electricity consumption dynamics and biogas utilisation across structurally different economies. This provides a basis for contextualising Ukraine's progress within the European energy transition landscape.

At the same time, analysing best practices and regulatory models implemented in these countries offers valuable insights into the effectiveness of policy instruments, technological pathways, and institutional support mechanisms. These insights can inform the formulation of recommendations for adapting successful approaches to the Ukrainian context, particularly in light of post-war recovery and strategic alignment with the EU Green Deal objectives.

The description of the variables used in the longitudinal model is presented in Table 2.

Table 2

Longitudinal model variables for Germany, Italy, France, and Poland

Variable	Symbols	Measurement unit	Data sources
Electricity consumption in the agricultural sector	electricity	GWh	Eurostat
Export of agricultural products	export	billion euro	Eurostat
Import of agricultural products	import	billion euro	Eurostat
Biogas electricity generation	biogas	GWh	Eurostat

Source: created by the authors.

To assess the distributional properties of the variables included in the longitudinal econometric model, the Jarque-Bera and Shapiro-Wilk tests were applied to test for conformity with the normality assumption. For those variables that did not satisfy the criteria for normal distribution, a Box-Cox transformation procedure was used. Specifically, null hypotheses were formulated concerning the value of the Box-Cox transformation parameter (λ). The outcomes of these tests enabled the determination of appropriate transformation strategies, most notably logarithmic transformation, aimed at achieving normality in the distribution of the model variables, thereby ensuring the validity of further econometric estimation and inference.

Unlike cross-sectional data, which consist of observations across n units at a single point in time, or time series data, which consist of observations over t time periods for a single unit, panel data incorporate observations on i units across t time periods. Such data are typically denoted as X_{it}, where $i = 1,2 \ldots, N; t = 1,2, \ldots, T$.

Most econometric methods applied to panel data require a balanced dataset, meaning that each cross-sectional unit has the same number of time observations. Regression models based on panel data are considered a powerful econometric tool, as they offer greater informational content and estimation efficiency under conditions of substantial variability and heterogeneity. Additionally, they help mitigate problems associated with omitted variables and multicollinearity.

The general form of a linear panel regression model is expressed as:

$$Y_{it} = \beta_0 + \beta X_{it} + u_{it}, \tag{2}$$

where variables Y and X have i and t indices for $i = 1,2, \ldots, N$ (cross-sections); $t = 1,2, \ldots, T$ (time series). The coefficients β_0 and β have no indices, assuming that they will be constant for all objects during the study period.

Linear panel regression was estimated using the following methods:

1) with the common constant β_0 in the equation *(the pooled OLS method)*:

$$Y_{it} = \beta_0 + \beta X_{it} + \varepsilon_{it,}\ E(\varepsilon|X) = 0 \tag{3}$$

2) fixed effects method:

$$Y_{it} = \beta_0 + \beta X_{it} + \alpha_i + \varepsilon_{it}\,, \tag{4}$$

where α_i the *n-1* objects are correlated with X_{it}.

OLS estimated the fixed effects model with dummy variables for n-1 objects (Least Squares Dummy Variable, LSDV, or Within Estimator):

$$\begin{aligned} Y_{it} - \bar{Y}_t = \beta_0 + \alpha_i + \beta X_{it} + \varepsilon_{it} - (\beta_0 + \alpha_i + \beta \bar{X}_\iota + \bar{\varepsilon}_\iota) = \\ = \beta(X_{it} - \bar{X}_\iota) + (\varepsilon_{it} - \bar{\varepsilon}_\iota) \end{aligned} \tag{5}$$

3) random effects method:

$$Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \tag{6}$$

$$Y_{it} = \beta_0 + \beta X_{it} + (v_i + \varepsilon_{it}), \tag{7}$$

where $\alpha_i = \beta_0 + v_i$; v_i – is a standardised random variable with zero expectation and constant variance ($\mu = 0; \sigma_v^2$).

The distinction between the two main approaches to panel data estimation lies in the source of heterogeneity across cross-sectional units. In the fixed effects method, each individual unit differs from others by a time-invariant constant, whereas in the random effects method, differences across units are captured by a random disturbance term v_i. A key limitation of the random effects model is its reliance on the assumption that the individual-specific error component is normally distributed, which may not always hold in empirical applications. Although OLS estimators in the random effects model are consistent, they are not efficient. Therefore, in practice, the random effects model is typically estimated using Generalized Least Squares (GLS), which accounts for heteroskedasticity and autocorrelation in the error structure, thus providing more reliable parameter estimates.

Fixed effects models are typically classified into two types: one-way and two-way models. One-way fixed effects models include an unobserved, time-invariant characteristic specific to each cross-sectional unit (in this case, each country), or a time fixed effect that is common across all units in a given time period, *t* (year). In contrast, a two-way fixed effects model incorporates both the unit-specific and time-specific effects simultaneously. A key challenge in estimating such models arises from the fact that these fixed effects are not directly observable and therefore cannot be estimated in a straightforward manner. To eliminate the fixed effects in a one-way model with time-invariant unit characteristics, the within-group (or "demeaned") transformation can be applied using the formula (5). The transformed model is then estimated using the OLS method. This transformation effectively removes the unobserved unit-specific effects a_i, allowing the model to capture only those characteristics that vary over time. Similarly, in the two-way fixed effects model, only the time-varying characteristics of the units are retained after the transformation, enabling consistent estimation of the model parameters.

An alternative to the within-group transformation method is the application of OLS with dummy variables for each cross-sectional unit or period, commonly referred to as the Least Squares Dummy Variables (LSDV) model. In this study, an LSDV model was constructed by introducing dummy variables for each country, where each country was represented by a separate binary (Boolean) variable. These dummies were incorporated into the primary dataset to account for unit-specific effects.

The pooled OLS regression model represents a basic form of OLS that does not account for the panel structure of the data. Pooled OLS is widely recognised as a baseline model in panel data analysis and is used in this study as a reference point for comparison with the results of more sophisticated estimation techniques. This model disregards time-specific and individual-specific effects unless explicitly included in the regression equation. Pooled OLS focuses solely on the relationship between the specified variables and assumes no correlation among the independent variables.

To determine the necessity of including fixed effects (i.e., individual intercepts for each cross-sectional unit) in the regression model, as opposed to a common intercept assumed in the pooled OLS approach, the standard F-test was applied. The null hypothesis in this context states that all individual intercepts are equal, thereby justifying the use of the pooled model with a shared constant term:

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_N. \tag{8}$$

To assess the relative suitability of the fixed effects panel model compared to the pooled model, the Wald test was conducted. This test evaluates the null hypothesis that all individual effects are jointly insignificant and thus unnecessary in the specification of the model.

The appropriateness of the random effects model was tested using the Breusch-Pagan Lagrange Multiplier test. The null hypothesis of this test posits the absence of random effects, while the alternative hypothesis supports the presence of significant random variation across individual units. The calculations were performed in the statistical package Stata 19. Figure 1 presents the conceptual research scheme for analysing the sustainable energy transition in agriculture in Ukraine and selected EU countries.

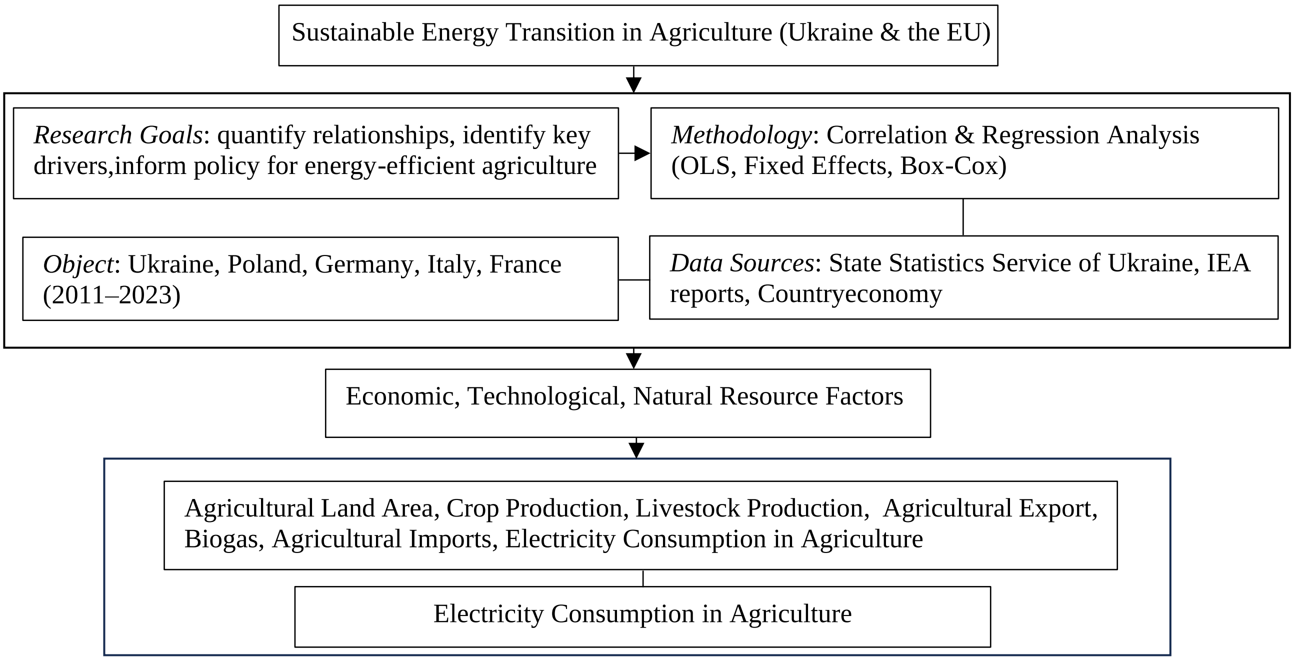


Figure 1. Conceptual research scheme for the sustainable energy transition in agriculture

Source: created by the authors.

It integrates the subject area, key concepts, and their interrelationships, linking research goals, objects of study, and methodological approaches with identified factor groups. It highlights how economic, technological, and natural resource factors feed into the assessment of electricity consumption in agriculture, thereby enabling the quantification of relationships, identification of key drivers, and formulation of policy recommendations for energy-efficient agricultural development.

4. RESULTS

4.1. Energy consumption in Ukraine's agricultural sector: econometric modelling and factor analysis.

4.1.1. Trends in electricity consumption in agriculture. To estimate the type of relationship between quantitative variables such as electricity consumption in the agricultural sector and the influencing factors listed in Table 1, in our case, a linear regression model was constructed based on data collected in Ukraine for 2012–2023. A linear regression model was chosen due to its interpretative clarity, confirmed linear relationships between the variables, and favourable statistical properties. Preliminary tests confirmed the normal distribution of key variables (or justified transformations), absence of multicollinearity, and homoscedasticity, making the linear model both statistically robust and practically informative for policy and management recommendations in the agricultural energy sector of Ukraine.

Figure 2 shows the dynamics of electricity consumption in the agricultural sector of Ukraine.

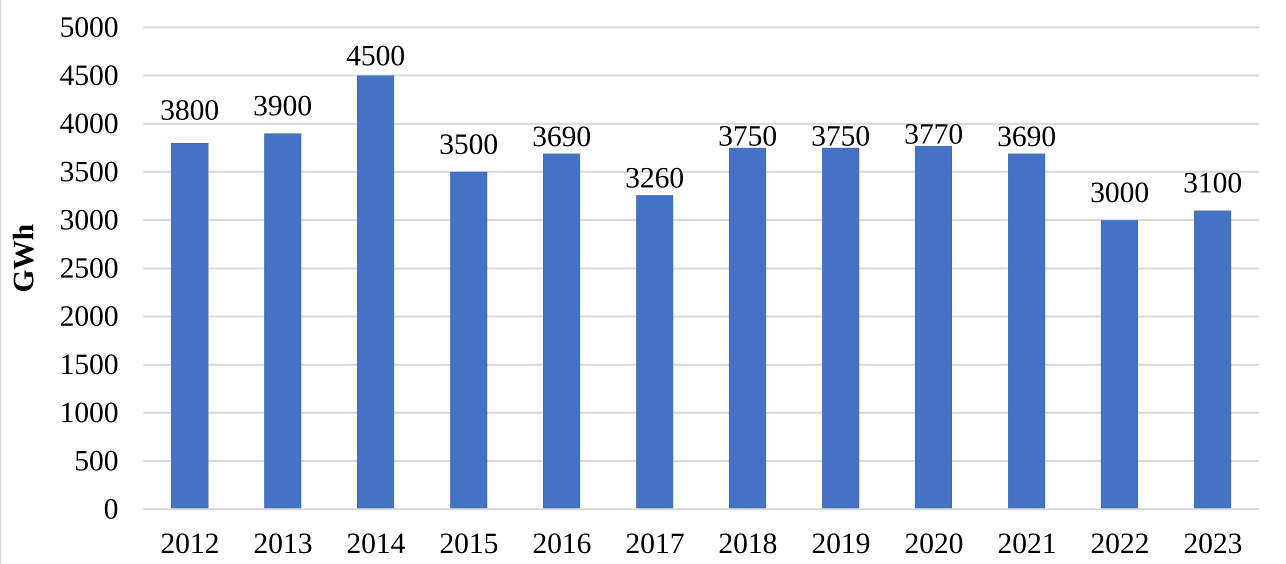


Figure 2. The dynamics of electricity consumption in the agricultural sector of Ukraine, GWh

Source: created by the authors based on State Statistics Service of Ukraine (n.d.).

Figure 2 illustrates the annual electricity consumption in Ukraine's agricultural sector from 2012 to 2023. Electricity consumption remained relatively stable at around 3,700–3,900 GWh during most of the analysed years, with minor fluctuations. The peak was observed in 2014 (4,500 GWh), while the lowest value was recorded in 2022 (3,000 GWh), largely due to the disruptions caused by the full-scale military invasion. In 2023, consumption showed a slight rebound to 3,100 GWh, indicating the beginning of a gradual recovery.

The period of 2012–2013 is characterised by a sharp economic downturn: Ukraine's growth virtually came to a halt, with GDP remaining at 0% in 2013. This was driven by structural changes, including a decline in demand for energy-intensive industries (such as metallurgy), high prices for imported energy resources, insufficient investment, a lack of deep reforms, as well as the onset of political and economic instability (mass protests, the annexation of Crimea, and the conflict in the east of the country), which led to the closure of energy-intensive Soviet-era enterprises and the destruction of infrastructure (IEA, 2020). Relative stabilisation was in 2014–2021 in energy use, with gradual adoption of energy-efficient technologies. In that period, improved energy management and optimisation of post-harvest processes, development of biogas and other renewable energy sources began moderating electricity demand. In 2022, the full-scale war resulted in the destruction of infrastructure, a reduction of industrial and agricultural operations, and limited access to energy. There are significant disruptions in electricity supply and logistics in agricultural regions. The year 2023 indicates the development of adaptive capacity of the agricultural sector, restoration of facilities, transition to decentralised energy sources (e.g., biogas, solar), and support for critical food supply chains. As a result, the overall trend reflects a transition from energy-intensive traditional agriculture to more adaptive and efficient practices shaped by political, economic, and military shocks. The role of energy diversification and decentralisation becomes increasingly significant in ensuring the sector's resilience.

Figure 3 presents the comparative dynamics of electricity consumption in the agricultural sector of Poland, Germany, Italy, and France over the period 2011–2023.

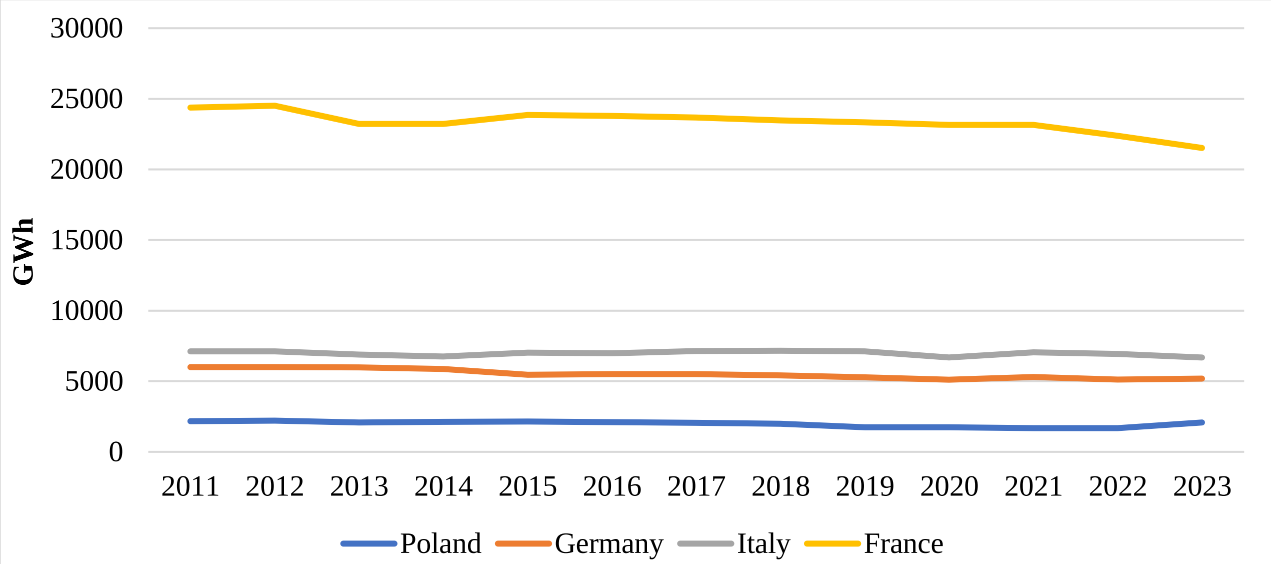


Figure 3. The dynamics of electricity consumption in the agricultural sector, GWh

Source: created by the authors based on Countryeconomy (2024).

The data, expressed in gigawatt-hours (GWh), show distinct national trends: France consistently demonstrates the highest consumption, though with a gradual decline over time, while Poland maintains the lowest values with relatively stable use until a slight increase in 2023. Germany and Italy occupy intermediate positions, exhibiting moderate fluctuations. This comparison highlights both structural differences in agricultural energy demand across the countries and the presence of gradual efficiency improvements or sectoral shifts influencing consumption patterns.

Figure 3 shows that, in comparison with Ukraine (see Figure 2), electricity consumption in the agricultural sector of France, Germany, and Italy is significantly higher throughout the analysed period, while Poland demonstrates levels closer to the Ukrainian trend. Ukraine's values fluctuate between 3,100–4,500 GWh, whereas France consistently exceeds 21,000 GWh, Italy remains in the range of 6,680–7,140 GWh, and Germany stays near 5,100–6,000 GWh. This gap highlights differences in agricultural scale, production intensity, and technological electrification among the countries.

4.1.2. Development of biogas production capacity. Figure 4 illustrates the dynamics of increasing installed biogas production capacity in the Ukrainian agricultural sector.

In Ukraine, official statistics and sectoral reports on biogas primarily present information in terms of installed capacity (MW) rather than actual annual production (GWh). This is largely due to the relatively young stage of the national biogas market, where complete and consistent data on generated electricity volumes are often unavailable, particularly in the early years of sector development. Using installed capacity data allows for the assessment of the potential production of biogas-based electricity and tracking of infrastructure expansion over time. While for the European

Union countries production volumes are commonly reported in GWh, reflecting real annual output and aligning with Eurostat and IEA statistical standards, the Ukrainian statistical framework prioritises technical capacity figures due to the reporting specifics and industry maturity level. Including MW values for Ukraine alongside GWh figures for the EU countries enables a balanced comparative analysis. Thus, we have done independent calculations for Ukraine and the EU countries (France, Germany, Italy and Poland). In both cases, the obtained results allowed assessing the impact of biogas production on agricultural electricity consumption.

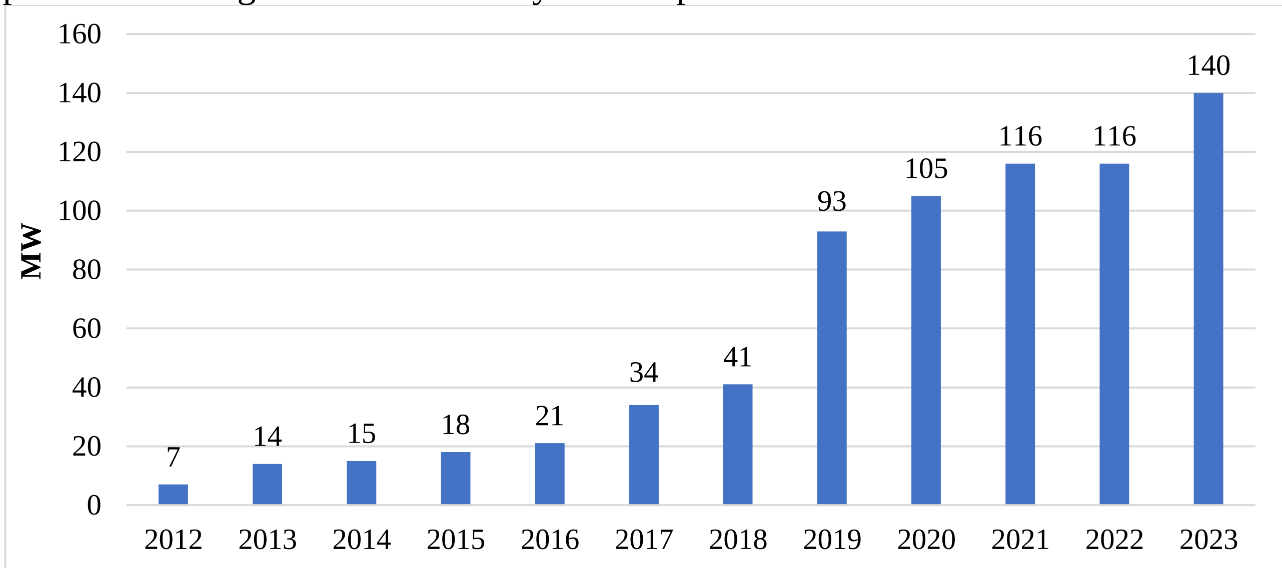


Figure 4. The dynamics of total installed electric capacity of biogas cogeneration units in Ukraine, MW (including agricultural and other feedstocks)

Source: created by the authors based on State Statistics Service of Ukraine (n.d.).

Figure 4 shows the increase in biogas production capacity in Ukraine's agricultural sector from 7 MW in 2012 to 140 MW in 2023. In Ukraine, the installed capacity of biogas plants operating on agricultural raw materials as of 2023 (the last period of the studied time series) was 31% of the total installed electric capacity of biogas plants. Based on State Statistics Service of Ukraine (n.d.), the data illustrate a slow but steady growth from 2012 to 2016, followed by accelerated development after 2017, especially between 2018 and 2020, when production more than doubled from 41 to 105 MW. The level remained stable at 116 MW in 2021 and 2022, with a significant leap to 140 MW in 2023.

The dynamics of biogas production in the Ukrainian agricultural sector over the period 2012–2023 demonstrate a clear upward trend, which can be divided into four distinct stages: the initial development phase, a period of accelerated growth, stabilisation, and a breakthrough expansion phase. During the initial stage (2012–2016), biogas capacity increased gradually from 7 MW to 21 MW. This period was characterised by forming the institutional and legal framework for renewable energy development, including introducing the "green tariff" and significant amendments to the Law of Ukraine on the Electric Power Industry (2010–2012). These measures laid the foundation for attracting investments into the biogas sector. Early pilot projects were implemented primarily at livestock farms, focusing on waste-to-energy conversion and localised energy supply.

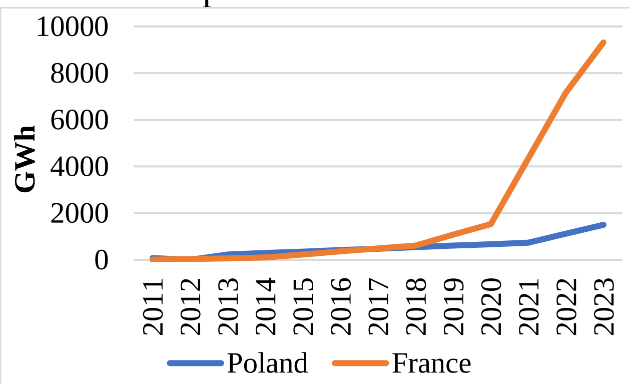
The acceleration phase (2017–2020) marked a significant increase in biogas capacity, with production rising from 34 MW in 2017 to 105 MW by 2020. Growing state and private investments, improvements in technological infrastructure, and progressive liberalisation of the Ukrainian energy market drove this surge. Large-scale biogas facilities were launched at intensive livestock and crop production enterprises, integrating circular economy principles and enhancing energy efficiency locally.

In 2021–2022, biogas production capacity stabilised at 116 MW. This plateau may be attributed to temporary market saturation in specific agricultural regions, logistical constraints, and rising economic uncertainty associated with the onset of full-scale war in 2022. Despite these challenges, the sector demonstrated resilience, maintaining stable generation levels amid national disruptions. The year 2023 witnessed a new growth phase, with installed biogas capacity rising to 140 MW. This breakthrough results from heightened demand for energy security and decentralisation and the mobilisation of international donor support for rural renewable energy initiatives. In April 2023, the agricultural company Hals Agro commissioned Ukraine's first biogas production facility by upgrading one of the plant's six existing biogas units.

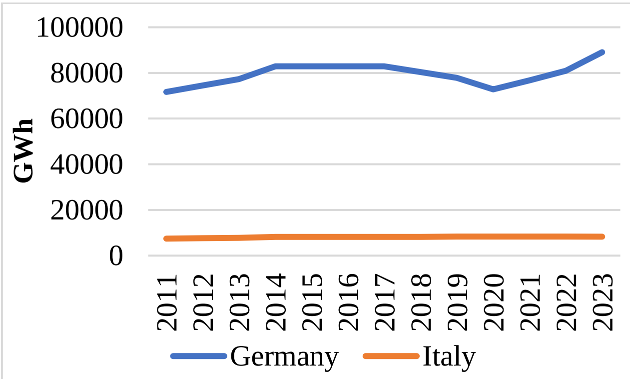
The station is expected to inject up to 3 million cubic meters of biogas annually into the Ukrainian gas distribution system. According to the Bioenergy Association of Ukraine, more than 70 biogas plants are currently operating in the country, with approximately 40 utilising agricultural biomasses as their primary feedstock (Bioenergy Association …, 2025). Biogas emerged as a vital component of adaptive energy strategies, particularly in war-affected areas, enabling farms to meet their electricity needs independently of centralised supply systems.

The observed trend confirms that biogas production has become a strategic pillar of Ukraine's sustainable agriculture. Its continued development contributes to energy diversification, greenhouse gas reduction, efficient use of agricultural waste, and the enhancement of rural energy autonomy – all of which are especially critical during systemic stress and reconstruction periods.

Figure 5 demonstrates the comparative trends in biogas production among selected European countries from 2011 to 2023.



a)



b)

Figure 5. The dynamics of biogas production, GWh

Source: created by the authors based on Petrykowska (2024); International… (2025).

Subfigure (a) highlights the rapid growth in France, especially after 2019, contrasted with the more gradual increase observed in Poland. Subfigure (b) shows that Germany maintains a consistently high production levels with slight fluctuations, while Italy demonstrates relatively stable but significantly lower production volumes. These patterns reflect differences in national renewable energy policies, infrastructure development, and market maturity within the biogas sector.

Figure 5 illustrates the actual biogas production in selected EU countries (GWh). France demonstrates a sharp increase after 2020, Poland shows gradual growth, Germany maintains a consistently high level with minor fluctuations, and Italy has moderate increases.

4.1.3. Descriptive statistics and data normality tests. The calculations were performed in the statistical package Stata 18. Summary statistics of the model variables are given in Table 2.

Table 2

Summary statistics of model variables

Variable	Mean	Standard deviation	Min	Max
Electricity	4.065	1.343	3.0	8.0
Export	19500000	4072854	13600000	27700000
Import	6000575	1692488	3484432	9300000
Area	41495.1	3111.6	32924.0	46800.0
Crops	125598.6	17276.8	107963.2	167336.0
Livestock	3254.8	136.5	2954.8	3445.5
Biogas	60.0	49.6	7.0	140.0

Source: created by the authors.

All variables have a positive mean value. Only one variable, biogas, deviates significantly from its mean value, which is explained by the rapid growth of installed biogas production capacity in Ukraine from 7 MW in 2012 to 140 MW in 2023. The results of validating the dependent variable, electricity, and the explanatory variables export, import, area, crops, livestock, and biogas for compliance with the normal distribution law using the Jarque-Bera and Shapiro-Wilk tests are given in Table 3.

Table 3

Results of validating whether the model variables conform to the normal distribution law

Variable	Jarque-Bera test		Shapiro-Wilk test		Is the distribution shape normal?
	χ^2	p-value	W	p-value	
Electricity	20.2100	0.0000	0.67167	0.0005	No
Export	0.5166	0.7724	0.95269	0.6765	Yes
Import	0.1006	0.9509	0.95618	0.7283	Yes
Area	10.8000	0.0045	0.70399	0.0009	No
Crops	3.5140	0.1726	0.86825	0.0621	Yes
Livestock	0.8202	0.6636	0.94371	0.5476	Yes
Biogas	1.5000	0.4724	0.84839	0.0351	No

Source: created by the authors.

Normality was confirmed for the variables export, import, crops, and livestock, as the p-values in the normality tests exceeded 0.05. In contrast, the dependent variable, electricity, as well as the explanatory variables, area and biogas, did not follow a normal distribution.

4.1.4. Correlational and regression analysis. The results of the correlation test between the explanatory variables and the dependent variable of the model are presented in Table 4.

Table 4

Results of testing the correlation of explanatory variables with the dependent variable of the model

Variable	Pearson correlation coefficient	p-value	Is there correlation?
Export	-0.2867	Non-significant	No
Import	0.6202	0.0500	Yes
Area	0.2329	Non-significant	No
Crops	-0.2422	Non-significant	No
Livestock	0.3197	Non-significant	No
Biogas	-0.5178	0.1000	Yes

Source: created by the authors.

According to the Chaddock scale, the values of Pearson correlation coefficients have the following interpretation: 0.1÷0.3 – weak correlation; 0.3÷0.5 – moderate correlation; 0.5÷0.7 – noticeable correlation; 0.7÷0.9 – high correlation; 0.9÷1.0 – strong correlation. According to the results presented in Table 4, the variables import (0.6202) correlate significantly and positively. The variable biogas (-0.5178) indicates an inverse relationship between installed biogas production capacity and electricity consumption in the agricultural sector.

Due to their non-significant correlation with the dependent variable electricity, the explanatory variables export, area, crops and livestock were excluded from further analysis. The remaining explanatory variable import show a positive correlation with the dependent variable electricity, while the variable biogas exhibits a negative correlation.

For the dependent variable, electricity, and the explanatory variable, biogas, both of which did not follow a normal distribution, null hypotheses concerning the Box-Cox transformation coefficient were tested. The results of these tests are presented in Table 5.

Table 5

P-value of the Box-Cox transformation coefficient

Variable	p-value			Type of transformation
	H0: $\lambda = -1$	H0: $\lambda = 0$	H0: $\lambda = 1$	
Electricity	0.123	0.011	0.000	Natural logarithm
Biogas	0.001	0.736	0.027	Natural logarithm

Source: created by the authors.

As shown in Table 3, both the dependent variable (*Electricity*) and the explanatory variable (*Biogas*) did not follow a normal distribution, which justified the application of the Box–Cox transformation. Table 5 shows that for *Electricity*, the null hypothesis

$\lambda = 0$ (log transformation) cannot be rejected ($p = 0.011 > 0.01$), while the null hypothesis $\lambda = 1$ (no transformation) was strongly rejected ($p = 0.000$), indicating that natural logarithm transformation is appropriate. For *Biogas*, the null hypothesis $\lambda = 0$ also cannot be rejected ($p = 0.736 > 0.05$), whereas the null hypothesis $\lambda = 1$ was rejected ($p = 0.027 < 0.05$), also supporting the use of a natural logarithm transformation. Consequently, both variables were transformed using the natural logarithm, ensuring improved normality and variance stabilisation, which increases the robustness and reliability of subsequent econometric estimations.

After the logarithmic transformations of the variables *electricity* and *biogas* were made, transformed variables *ln_electricity* and *ln_biogas* were included in the model instead initial variables *electricity* and *biogas*, and the linear regression model parameters were estimated using the least squares method. The estimated parameters of the final econometric model are given in Tables 6 and 7.

Table 6

Statistical characteristics of the regression model

Number of observations	12
F (2.9)	49.10
Prob > F	0.0000
R-squared	0.9160
Adj R-squared	0.8974
Root MSE	0.0840

Source: created by the authors.

The obtained linear regression model demonstrates a very high explanatory power and is statistically significant ($F = 49.10$, $p < 0.001$). The adjusted coefficient of determination (R^2_{adj}) equals 0.8974, indicating a high explanatory power of the model and confirming that approximately 89.7% of the variation in the dependent variable is accounted for by the selected independent variables (import and biogas capacity). The Root Mean Square Error indicates a low level of forecast error, which confirms the model's reliability.

Table 7

Estimated parameters of the constructed regression model

Variable	Coefficient	Standard error	t	P>|t|	[95% conf. interval]
Import	0.0000000965	0.000000015	6.45	0.000	[0.0000000645, 0.000000130]
Ln_biogas	-0.1921707	0.0246136	-7.81	0.000	[-0.2478506, -0.1364908]
Const.	1.493064	0.1269398	11.76	0.000	[1.205907, 1.780222]

Source: created by the authors.

According to the results presented in Table 7, the import of agricultural products (*import*) positively significantly ($\alpha = 0.001$) affect the dependent variable. The explanatory variable *ln_biogas* has a significant negative effect ($\alpha = 0.001$) on the dependent variable. The equation of the constructed econometric model has the following specification:

$$ln(electricity) = 1.493064 + 0.0000000965 * import - 0.1921707 \cdot \cdot ln\,(biogas).$$

The Fisher's F-test gave a test statistic of 49.10 with a p-value = 0.000, i.e. the parameter estimates of the constructed econometric model are jointly significant at $\alpha = 0.001$. The results of the test for the presence of collinearity between the independent variables in the constructed econometric model are given in Table 8.

Table 8

Results of testing multicollinearity of independent variables of the model

Variable	VIF	1/VIF
Import	1.00	0.997989
Ln_biogas	1.00	0.997989
Mean VIF	1.00	-

Source: created by the authors.

The low value of the calculated VIF indicates the absence of multicollinearity among the explanatory variables in the constructed econometric model. The Breusch-Pagan and White tests confirmed the hypothesis of homoscedasticity of the residuals of the constructed econometric model. The Jarque-Bera and Shapiro-Wilk tests confirmed the hypothesis of compliance of the residuals of the constructed econometric model with the normal distribution law.

When interpreting the estimated parameters of the constructed econometric model, we have the elasticity of the variable biogas as "log-log" and the semi-elasticity of the variables import as "log-level". Thus, an increase in the installed capacity of biogas production (biogas) by 1% leads to a decrease in the consumption of electricity in the agricultural sector (electricity) by 0.1921707%. An increase in the import of agricultural products (import) by one unit (thousand USD) leads to an increase in the consumption of electricity in the agricultural sector (electricity) by $0.0000000965 \cdot 100\% = 0.00000965\%$.

The received empirical results for Ukraine allow us to conclude that there is a positive correlation relationship between the variables import (0.6202) and an inverse relationship (-0.5178) between the installed capacity of biogas production (*biogas*) and electricity consumption (*electricity*). The results suggested that an increase in the import of agricultural products leads to an increase in electricity consumption. This is explained by the fact that the needs of mechanisation, automation, and infrastructure directly depend on the energy supply. In turn, introducing biogas technologies contributes to a decrease in electricity consumption since agricultural enterprises can produce energy independently.

4.2. Comparative analysis of electricity consumption in the agricultural sector of the EU countries: fixed effects and the role of biogas.

4.2.1. Constructing longitudinal models. To estimate the type of relationship between quantitative variables such as electricity consumption in the agricultural sector of the European countries (Germany, France, Italy, Poland) and the influencing factors listed in Table 2, longitudinal models (Pooled OLS, Least Square Dummy

Variable, Random Effects) were constructed based on panel data collected for 2011–2023.

The results of validating the dependent variable, electricity, and the explanatory variables, biogas, export, and import, for compliance with the normal distribution law using the Jarque-Bera and Shapiro-Wilk tests are given in Table 10.

Table 10

Results of validating whether the model variables conform to the normal distribution law

Variable	Jarque-Bera test		Shapiro-Wilk test		Is the distribution shape normal?
	χ^2	p-value	W	p-value	
Electricity	9.722	0.0077	0.73119	0.0000	No
Biogas	12.120	0.0023	0.64022	0.0000	No
Export	2.065	0.3560	0.97225	0.2625	Yes
Import	2.335	0.3111	0.96717	0.1600	Yes

Source: created by the authors.

Normal distribution was confirmed for the variables export, import (p-value in tests > 0.05). In turn, the dependent variable, electricity and the explanatory variable, biogas, don't correspond to the normal distribution law.

The results of the Pearson correlation test between the explanatory variables and the dependent variable of the model are presented in Table 11.

Table 11

Results of testing the correlation of explanatory variables with the dependent variable of the model

Variable	Pearson correlation coefficient	p-value	Is there correlation?
Export	0.2755	0.05	Yes
Import	0.1628	Non-significant	No
Biogas	-0.2864	0.05	Yes

Source: created by the authors.

The results in Table 11 show that the dependent variable (electricity consumption in agriculture) has a weak but statistically significant positive correlation with agricultural exports (Pearson $r = 0.2755$, $p = 0.05$) and a weak but statistically significant negative correlation with biogas production (Pearson $r = –0.2864$, $p = 0.05$). In contrast, the correlation between electricity consumption and agricultural imports is positive but not statistically significant ($p > 0.05$), indicating no meaningful linear relationship. According to the Chaddock scale, the significant correlations observed are weak in strength, suggesting that while exports and biogas are related to electricity consumption, other factors likely play a more substantial role in explaining its variation.

For the dependent variable, electricity, and the explanatory variable, biogas, which didn't correspond to the normal distribution law, the null hypotheses regarding the value of the Box-Cox λ transformation coefficient were tested. The test results are given in Table 12. After the logarithmic transformations of the variables electricity and biogas were made, transformed variables *ln_electricity* and *ln_biogas* were included in the model instead initial variables *electricity* and *biogas*.

Table 12

P-value of the Box-Cox transformation coefficient

Variable	p-value			Type of transformation
	H0: λ = -1	H0: λ = 0	H0: λ = 1	
Electricity	0.000	0.598	0.000	Natural logarithm
Biogas	0.000	0.371	0.000	Natural logarithm

Source: created by the authors.

The results of constructing Pooled OLS are presented in Table 13. According to the results, the explanatory variable *ln_biogas* negatively significantly ($\alpha = 0.001$) and the explanatory variable *export* positively significantly ($\alpha = 0.001$) affect the dependent variable.

Table 13

Results of constructing Pooled OLS

Variable	Ln_electricity	
	Coefficient	p-value
Ln_biogas	-0.1895	0.000
Export	0.0392	0.000
Const.	1.7821	0.000
Number of observations	52	
R-squared	0.4115	
Adj R-squared	0.3875	

Source: created by the authors.

The results of the test for the presence of collinearity between the independent variables in the constructed econometric model are given in Table 14.

Table 14

Results of testing multicollinearity of independent variables of the model

Variable	VIF	1/VIF
Export	1.62	0.618958
Ln_biogas	1.62	0.618958
Mean VIF	1.62	-

Source: created by the authors.

The low value of the calculated Variance Inflation Factor indicates the absence of multicollinearity among the explanatory variables in the Pooled OLS model, thereby confirming the stability and reliability of the estimated coefficients.

To evaluate the adequacy of the Pooled OLS model, diagnostic measures such as the adjusted R-squared and the F-test were used. The adjusted R-squared value was 0.3875, indicating that approximately 38.75% of the variation in the dependent variable is explained by the model, which is considered satisfactory for panel data analysis. The F-test yielded a test statistic of 17.13 with a corresponding p-value of 0.00, thereby confirming the joint statistical significance of the estimated coefficients at the $\alpha = 0.001$ significance level. The equation of the constructed econometric model has the following specification:

$$ln(electricity) = 1.782139 + 0.0392004 \cdot export - 0.1894839 \cdot ln\,(biogas).$$

When interpreting the estimated parameters of the constructed longitudinal model, we have elasticity of the variable biogas as "log-log" and semi-elasticity of the variable export as "log-level". Thus, an increase in the biogas electricity generation (biogas) by 1% leads to a decrease in the consumption of electricity in the agricultural sector (electricity) by 0.1894839%. An increase in the export of agricultural products (export) by one unit (billion euros) leads to an increase in the consumption of electricity in the agricultural sector (electricity) by $0.0392004 \cdot 100\% = 3.92004\%$.

The results of building the LSDV model are presented in Table 16.

Table 16

Results of LSDV model

Variable	Ln_electricity	
	Coefficient	p-value
Ln_biogas	-0.00922	0.194
Export	0.00129	0.108
France	1.28478	0.000
Germany	0	-
Italy	0.20588	0.000
Poland	-0.78827	0.000
Const.	1.89817	0.000
Number of observations	52	
R-squared	0.9965	
Adj R-squared	0.9961	

Source: created by the authors.

The adjusted R-squared of the model is 0.9961, indicating that 99.61% of the variation in the dependent variable is explained by the independent variables, which reflects a high level of explanatory power. The *F*-test produced a test statistic of 2613.74 with a corresponding p-value of 0.00, confirming the joint statistical significance of the model coefficients at the $\alpha = 0.001$ significance level. The results of constructing a regression model with random effects are presented in the Table 17.

Table 17

Results regression model with random effects

Variable	Ln_electricity	
	Coefficient	p-value
Ln_biogas	-0.00922	0.188
Export	0.00129	0.101
France	2.07305	0.000
Germany	0.78827	0.000
Italy	0.99415	0.000
Poland	0	-
Const.	1.10990	0.000
Number of observations	52	

Source: created by the authors.

It is widely recognised that the R-squared is not an appropriate measure for assessing the goodness of fit in random effects models, as regressions estimated using the Generalized Least Squares (GLS) method do not yield reliable R-squared statistics. Instead, the overall significance of the model is more accurately evaluated using the

Wald statistic. In this case, the Wald test yields a value of 13.0687 with a p-value of 0.00, indicating that the regression is jointly significant at conventional levels.

4.2.2. Comparative assessment and selection of panel data estimation technique. A pairwise comparison of the previously estimated models – Pooled OLS, fixed effects, and random effects – was conducted to determine the most appropriate specification. The result of the Broisch-Pagan test for the presence of a random individual effect, presented in Table 18, showed a p-level = 1.00. Thus, the null hypothesis of the absence of random individual effects was confirmed. The pooled model describes our data better than the random effects model.

Table 18

Results of Broisch-Pagan test

Variable	Estimated results	
	Var	SD = sqrt (Var)
Ln_electricity	0.57712	0.75968
Error	0.00224	0.04737
Random effects error	0	0

Source: created by the authors.

The Pooled OLS model was compared with the fixed effects regression model using the Wald test, which evaluates the null hypothesis of no individual (cross-sectional) effects. The results of this test, presented in Table 19, were used to assess the statistical necessity of including fixed effects in the model specification.

Table 19

Results regression model with fixed effects

Variable	Ln_electricity	
	Coefficient	p-value
Ln_biogas	-0.00922	0.194
Export	0.00129	0.108
Const.	2.07377	0.000
Number of observations	52	
Wald test (F-test that all $\alpha_i = 0$)	F (3.46) = 2557.32 p-value = 0.0000	

Source: created by the authors.

Given that the p-value equals 0.00, the null hypothesis is rejected. This result indicates that the fixed effects regression model provides a superior fit to the data compared to the Pooled OLS model. Consequently, the fixed effects model (LSDV) was selected as the final specification. Based on the estimated coefficients presented in Table 16, the corresponding regression equation takes the following form:

$$\ln(electricity) = 1.898173 - 0.092224\ln(biogas) +$$
$$+ 0.0012887 export + 1.284782 France + 0,2058758 Italy - 0.7882711 Poland.$$

The coefficients associated with the dummy variables for France, Italy, and Poland, are statistically significant at the 0.001 significance level. Notably, in the estimated LSDV model, the coefficient associated with the dummy variable for Poland is negative. This indicates that, holding the explanatory variables *ln_biogas* and *export* constant, electricity consumption in Poland's agri-food sector is lower than that of Germany, France, and Italy. Accordingly, it can be concluded that, under equivalent levels of biogas-based electricity generation and agri-food export volumes, Poland shows more favourable conditions for reduced energy consumption in the agri-food sector, captured by the fixed effects, than the other examined countries.

5. DISCUSSION

The empirical findings of this study confirm that agricultural imports and livestock production are positively associated with electricity consumption in Ukraine's agricultural sector, while biogas capacity demonstrates a negative relationship. These results are consistent with global research trends highlighting the interplay between agricultural development, energy use, and renewable energy integration. In particular, the study by Zhang et al. (2025), using panel data from China, found that rural households are highly sensitive to socio-economic determinants and energy pricing policies, which parallels Ukraine's agricultural sector, where production intensity and imports significantly influence electricity demand. As in Ukraine, energy vulnerability in rural zones is linked to broader economic and infrastructural dynamics. Additionally, Adinkrah et al. (2025) emphasise that reliable access to electricity is a foundational element for national progress and sectoral planning. Their study shows how machine learning and AI-driven forecasting tools can help optimise rural energy use and enable more accurate electricity planning. These insights support our conclusion that electricity demand in agriculture can be better managed through data-based policy and infrastructure development. The role of renewable energy in reducing electricity dependency is also supported by Abouaiana et al. (2025), who underline the potential of rural regions as platforms for implementing clean energy projects. Their analysis of energy intensity in rural buildings highlights technological factors-similar to biogas adoption in Ukraine, as decisive in lowering electricity consumption, validating our model's negative elasticity for biogas capacity. In contrast, Manasseh et al. (2024) point out that increased electricity generation does not automatically lead to agricultural growth, primarily due to insufficient infrastructure and unequal distribution. This aligns with our findings, which indicate that while overall electricity generation capacity may be growing, decentralised, farm-level biogas production plays a more direct and effective role in reducing grid dependency and improving sectoral resilience.

The obtained results can be explained by the specific structural and policy conditions in the European Union energy sector. Countries such as Denmark and Germany exemplify how long-term policy support, technological innovation, and institutional maturity foster high efficiency in biogas use. Denmark's Biogas Outlook 2024 demonstrates that upgraded biogas accounted for nearly 40% of the national gas consumption in 2023 (rising to 45% with off-grid use), highlighting the maturity of its integration into the energy system (Biogas Danmark, 2024). Similarly, Germany, with more than 9,500 farm-scale biogas plants, has strengthened its gas supply security and demonstrated resilience through decentralised infrastructure (Thrän et al., 2023). These country-level experiences resonate with our findings, where higher biogas capacities correlate with lower energy intensity and improved electricity system performance.

The advantages of our approach compared to similar studies lie in the use of integrated econometric modelling with Box-Cox transformations, which allowed us to account for non-normal distributions and improve robustness. Previous works, such as Bórawski et al. (2024), concentrated primarily on long-term forecasts of biogas-based electricity generation, while our study provides empirical validation of its interrelation with agricultural trade and electricity consumption patterns, thus covering an underexplored nexus. Likewise, Gustafsson & Anderberg (2022) highlighted that differences in EU biogas development are primarily shaped by policy instruments such as feed-in tariffs and subsidies; our findings complement this by quantifying the impact of structural efficiency beyond policy alone.

The results also contribute to closing the research gap defined in Section 2, namely the limited understanding of the interplay between biogas production and broader electricity market dynamics. By linking agricultural biogas generation to both electricity intensity and trade indicators, our study demonstrates that sustainable energy transitions can mitigate sectoral inefficiencies. This is particularly important in the context of EU climate policies, which Bórawski et al. (2024) identify as a primary driver of growth in specific member states.

Overall, these comparative insights reinforce the robustness of the current study's conclusions. They suggest that advancing biogas infrastructure and supporting rural electrification strategies could not only reduce energy costs and improve sustainability but also enable strategic energy transitions in Ukraine's agricultural sector. Future research should continue integrating AI-based forecasting and regionally adaptive policies to expand the empirical base and enhance practical energy planning tools.

Nevertheless, some limitations must be acknowledged. First, the comparability of results across EU countries is constrained by divergent policy frameworks (Gustafsson & Anderberg, 2022) and varying levels of infrastructure maturity. Second, while Denmark and Germany serve as positive benchmarks, the applicability of their models to less developed contexts remain uncertain. Third, as with any empirical econometric model, our estimates depend on the quality and scope of available data. This may limit the generalisability of results, particularly when projecting long-term effects beyond the studied period. Despite these constraints, the study offers novel insights into the biogas – electricity – trade nexus, reinforcing the need for integrated policy design that links renewable energy deployment with agricultural and industrial strategies.

6. CONCLUSIONS

The results of the econometric analysis confirm the presence of statistically significant relationships between electricity consumption in Ukraine's agricultural sector and key economic and energy indicators. Specifically, agrarian import volumes and livestock production positively influence electricity demand, reflecting the energy-intensiveness of post-harvest processing, feed production, refrigeration, and mechanised animal husbandry operations. Conversely, installed biogas production capacity demonstrates a significant negative relationship with electricity consumption, indicating its growing role in substituting conventional energy sources and supporting the decentralisation of energy supply in agriculture. The model's high explanatory power (Adjusted $R^2 = 0.8974$) and overall statistical significance ($F = 49.10$, $p < 0.001$) reinforce the robustness of the findings. All included variables passed normality and homoscedasticity tests, and no multicollinearity was detected. The elasticity analysis further substantiates the practical relevance of biogas development: a 1% increase in installed biogas capacity leads to a 0.192% reduction in electricity consumption, underscoring its strategic value in reducing energy dependence and enhancing resilience during systemic disruptions.

The econometric analysis conducted using longitudinal panel data for Germany, France, Italy, and Poland (2011–2023) confirms the statistically significant influence of biogas-based electricity generation and agricultural exports on electricity consumption in the agricultural sector. The most appropriate model specification identified through rigorous testing – including the Wald and Breusch-Pagan tests – was the fixed effects model, which demonstrated a high explanatory power (Adjusted $R^2 = 0.9961$) and joint statistical significance of the estimated parameters ($F = 2613.74$, $p < 0.001$). The negative and statistically significant coefficient for the dummy variable associated with Poland suggests that, under equivalent levels of biogas electricity generation and export intensity, Poland demonstrates lower electricity consumption in agriculture compared to the benchmark country (Germany). This means that Poland has more favourable structural or technological conditions that allow for more efficient energy use in its agri-food sector. The integration of country-specific effects through the LSDV model reveals substantial heterogeneity in energy consumption patterns across EU member states. These insights underline the importance of tailoring national energy policies in agriculture to account for country-specific factors, particularly regarding renewable energy deployment and export-driven electricity intensity.

These findings provide quantitative evidence of the drivers of electricity consumption in agriculture and highlight the importance of energy diversification through bioenergy. The observed trends support policy recommendations to stimulate biogas investments, modernise energy infrastructure, and integrate renewable energy into the agricultural value chain.

This study emphasises the importance of a comprehensive approach to assessing the impact of agricultural activities on electricity consumption, considering economic, technological, and natural resource factors, as well as the role of biogas production as an alternative energy source. In particular, the research focuses on identifying the key drivers behind the growth in agricultural energy demand, evaluating opportunities to enhance energy efficiency, and integrating renewable energy sources – including biogas – into the energy consumption structure of the agricultural sector. Accordingly, the study contributes to the development of a scientifically grounded energy management policy for Ukraine's agrarian sector, oriented towards sustainable development and energy security.

The results have a broad range of practical applications in agricultural management, strategic planning, and policymaking. Specifically, the empirical findings can be utilised at different levels of decision-making:

1. National agrarian and energy policy: to inform strategies for the energy-efficient development of Ukraine's agricultural sector, support policies for bioenergy development (particularly biogas production), and contribute to national energy transition plans aligned with the sector's needs and potential.

2. Local governments and regional programs: for planning energy infrastructure in rural communities, supporting local initiatives to implement biogas plants, and optimising energy use at the community level.

3. Businesses and agricultural enterprises: to guide investment decisions in energy infrastructure (biogas, solar power plants, and modernisation), conduct energy audits of farms, identify opportunities to reduce electricity consumption without compromising productivity, and improve the competitiveness of agricultural production by lowering energy costs.

4. International cooperation and European integration: to support the preparation of reports and project proposals under EU cooperation frameworks – particularly for fulfilling the European Green Deal commitments – and to attract investments in bioenergy projects based on empirically grounded conclusions.

Thus, the study serves as a practical tool for managers, investors, policymakers, and researchers striving to promote the energy-efficient and environmentally sustainable development of Ukraine's agricultural sector.

7. LIMITATIONS AND FUTURE RESEARCH

While this study offers valuable insights into the relationship between agricultural development and electricity consumption in Ukraine, it also has several limitations that should be acknowledged. First, the analysis is based on a small sample size (2012–2023), which may limit the generalisability of the findings and the statistical robustness of the results. Future studies should consider extending the time series or incorporating panel data to enhance reliability. Second, although the model includes key economic, technological, and natural-resource indicators, it does not account for regional heterogeneity, climatic conditions, or policy shifts that may influence electricity demand across different agricultural zones. Incorporating spatial or regional econometric techniques could help capture these disparities. Third, the variable representing biomethane reflects only installed capacity, not actual energy output or utilisation efficiency. Future research should explore more detailed energy performance indicators, including operational characteristics of renewable energy facilities and their integration into farm energy systems. Overall, future research should aim to expand the empirical base, integrate cross-country comparisons, and evaluate the role of other renewable energy sources to support the development of a resilient and energy-efficient agricultural sector.

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